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Computer-Aided Design AND APPLICATIONS

Intelligent Exploration of Environmental Design: Combining CAD Modeling and Reinforcement Learning Technology

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Abstract. This article aims to explore the implementation process and effectiveness of intelligent environment design through simulation experiments. To achieve this goal, the article first outlines the importance of intelligent environment design and its current research status in the field and proposes a research method that combines CAD modelling and reinforcement learning algorithms. During the research process, a complete implementation process covering requirements analysis, CAD modelling, reinforcement learning optimization, and design solution output was designed, with a particular emphasis on the importance of continuously adjusting and optimizing the model throughout the entire process to improve design efficiency and solution quality. The experimental results show that the effective combination of CAD modelling technology and reinforcement learning algorithms can significantly improve the design efficiency of intelligent environment design models while optimizing design solutions to meet diverse user needs. The average score for intelligent design methods reached 9.3 points, while the average score for traditional design methods was only 7.5 points. This study offers fresh insights and methodological direction for both research and practical applications within the pertinent fields.

Keywords: Environmental Design; Intelligent Exploration; CAD Modeling; Reinforcement Learning
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1 INTRODUCTION

As science and technology rapidly evolve, intelligence has increasingly emerged as a focal point of research across diverse disciplines. Environmental design encompasses the creation of spatial environments that cater to both material and spiritual human needs through techniques such as planning, designing, and decorating. It spans fields like architecture, interior design, and landscape design, aiming to forge comfortable, aesthetically pleasing, and practical living and working environments. Chen et al. [1] explored machine learning-based research in the field of machine tools and analyzed its application prospects in the new-generation information technology environment. By using machine learning technology, real-time monitoring and analysis of machine tool operation data can be carried out, potential faults can be detected on time, and early warning can be given. This can not only reduce the probability of faults occurring but also lower maintenance costs and improve production efficiency. By using machine learning algorithms to learn a large amount of data during the machining process, intelligent adjustment of machining parameters can be achieved, thereby improving machining accuracy and efficiency. In the new generation of information technology environment, research in the field of machine tools will pay more attention to data collection and analysis. By using IoT technology to achieve real-time communication between machine tools and cloud platforms, richer data resources can be collected. Meanwhile, by utilizing big data and cloud computing technology to analyze and process these data, more valuable information can be extracted, providing a richer dataset for the training of machine learning algorithms. As people's living standards and aesthetic preferences evolve, environmental design increasingly emphasizes personalization and humanization, thereby demanding greater creativity and design expertise from practitioners.

With the rapid development of science and technology, vehicular edge computing (VEC) and network environment content caching are becoming important parts of intelligent transportation systems. In order to improve the performance and efficiency of onboard edge computing further, Dai and Xu [2] analyzed the content caching of deep reinforcement learning and licensing blockchain in onboard edge computing and the network. Through this approach, vehicles can process and analyze data faster, thereby improving the overall efficiency of the transportation system. Content caching refers to storing popular content in vehicles or roadside units in the onboard edge computing environment to quickly respond to vehicle requests. Deep reinforcement learning is a technology that combines deep learning and reinforcement learning. It approximates the value function or policy function in reinforcement learning through deep neural networks, thereby solving decision problems in complex environments. In the content cache of onboard edge computing, deep reinforcement learning can help the system intelligently select which content should be cached, when and where to maximize the cache efficiency and reduce the delay of content requests. Being intimately linked to human life, the intelligent exploration of environmental design holds significant potential for enhancing design efficiency, optimizing design solutions, and catering to the individual needs of users. Deep Reinforcement Learning (DRL) and Mixed Reality (MR) are gradually becoming two key technologies that change the way we interact with the digital world. Combining these two, Devo et al. [3] constructed an intelligent image environment that not only has high autonomy but also provides a rich and immersive user experience. Deep reinforcement learning combines the representation learning ability of deep learning with the decision-making ability of reinforcement learning, allowing agents to learn how to make the best decisions through trial and error in complex, unknown environments. In the exploration of image environments, deep reinforcement learning can learn how to identify key information, plan paths, and interact with the environment, thereby achieving efficient exploration and learning. By combining deep reinforcement learning with mixed reality, an intelligent image environment with high autonomy and immersive experience can be constructed. In this environment, agents can learn how to interact with the environment through deep reinforcement learning while utilizing the rich visual and auditory information provided by mixed reality to perceive and understand the environment. This combination can not only improve the exploration efficiency and learning effectiveness of intelligent agents but also provide users with a more realistic and natural interactive experience.

On the other hand, reinforcement learning is a machine learning algorithm that enables agents to learn optimal decision-making strategies through interaction with their environment. In this paradigm, agents select and execute actions based on their current state, receive rewards or punishments from the environment based on these actions, and adjust their strategies accordingly to maximize cumulative rewards. With the rapid development of digital technology, the field of indoor environmental design has also undergone tremendous changes. As a leader in CAD (Computer Aided Design) modelling technology, Farooq et al. [4] provide designers with a brand-new design tool. CAD modelling technology has a wide range of applications in indoor environment design. Firstly, in terms of spatial planning, designers can quickly generate multiple spatial layout schemes through CAD modelling software and compare and optimize them. This helps designers better understand spatial relationships, improve space utilization, and create a more comfortable and practical indoor environment for customers. Secondly, in terms of material selection and matching, CAD modelling technology provides designers with more choices. Designers can use software to apply different materials to models and observe their visual and matching effects. This virtual trial and error process not only helps designers quickly find the best material matching scheme but also provides customers with a more diverse range of material choices. In addition, CAD modelling technology also plays an important role in lighting design. Designers can simulate lighting effects through software, arrange the position and angle of lighting fixtures reasonably, and create a warm and comfortable lighting atmosphere. This lighting design not only improves the comfort of the indoor environment but also helps to create different spatial atmospheres and styles. Reinforcement learning has achieved notable successes in various domains, including game AI and autonomous driving. In recent years, distributed model-free deep reinforcement learning has shown great potential in the field of robot control, especially in dealing with complex and uncertain environments. Felbrich et al. [5] explored how to utilize this technology to achieve additive manufacturing of autonomous robots in computational design environments. Distributed model-free deep reinforcement learning is a technique that enables robots to learn how to make optimal decisions while interacting with the environment. This method does not require providing precise mathematical models for the robot in advance but rather allows the robot to try different actions in actual or simulated environments and adjust its decision-making strategy based on feedback results. The computational design environment is a virtual and controllable simulation environment used to simulate the real additive manufacturing process. This environment allows researchers to test and optimize algorithms without affecting the real world. By adjusting parameters and conditions in the environment, researchers can simulate various challenges and uncertainties that may arise in practical scenarios, thereby evaluating the performance and robustness of algorithms. In intelligent environmental design, reinforcement learning can be used to optimize the design scheme and improve the design efficiency.

In environmental design, CAD modelling technology is widely used in building model construction, indoor layout design and so on. As an important means of modern design, the combination of CAD modelling technology and artificial intelligence technology, such as reinforcement learning, provides new possibilities for the intelligence of environmental design. Reinforcement learning, as an advanced machine learning technology, provides an effective solution for adaptive environmental control of intelligent vehicles. Hu et al. [6] explored reinforcement learning methods for designing practical adaptive environmental control for intelligent vehicles. Reinforcement learning is a technique of learning through trial and error, where agents interact with the environment by executing actions, observing results, and adjusting strategies to maximize long-term returns. In smart cars, reinforcement learning can help vehicles learn how to make optimal driving decisions based on real-time environmental information, such as road conditions, traffic signals, other vehicles, and pedestrians. Intelligent vehicle adaptive environmental control faces many challenges, such as complex and ever-changing road environments, uncertain traffic participant behaviours, and real-time requirements. In the process of reinforcement learning, agents need to strike a balance between exploring new strategies and utilizing known optimal strategies. We can adopt some classic exploration strategies, such as ε, the greedy strategy, aiming to gradually approach the optimal strategy while maintaining a certain level of exploration. The aim of this study is to investigate the utilization of CAD modelling alongside reinforcement learning technology in intelligent environmental design. Through simulation experiments, we aim to validate its feasibility and efficacy, ultimately providing a solid theoretical and practical foundation for advancing the intelligent progression of environmental design.

Our research encompasses several key aspects: analyzing the requirements and obstacles inherent in intelligent environmental design, formulating an intelligent environmental design model that integrates CAD modelling with reinforcement learning, and devising simulation experiments to assess the model's viability and performance. Our innovation lies in the introduction of reinforcement learning into the realm of environmental design, its fusion with CAD modelling, and the realization of intelligent, optimized design processes. Furthermore, we propose an evaluation methodology for intelligent environmental design schemes grounded in simulation experiments, elevating the scientific rigour and precision of design assessments.

The article is structured into six parts. Part one introduces the research background, its significance, content, and innovations. Part two presents a review of the current research landscape. Parts three through five comprise the article's core, discussing the establishment of the intelligent environmental design model, its implementation through the integration of CAD modelling and reinforcement learning, and the simulation experimental research, respectively. Finally, part six concludes the study, summarizing findings, acknowledging limitations, and charting future directions for research.

2 RELATED WORK

In order to achieve efficient, reliable, and adaptive connectivity of IoT devices, deep reinforcement learning methods have become an important technological approach. Kwon et al. [7] explored how to use deep reinforcement learning methods to design intelligent connections in IoT environments. The Internet of Things environment is composed of a large number of heterogeneous devices, which have different communication protocols, functional requirements, and resource limitations. In such an environment, achieving intelligent connections between devices faces many challenges, such as compatibility between devices, communication efficiency, energy management, and so on. Deep reinforcement learning combines the advantages of deep learning and reinforcement learning and can handle high-dimensional state spaces and complex decision-making processes. In the Internet of Things environment, it can model the connection problem between devices as a Markov decision process (MDP), where device status, connection actions, and connection effects are key elements. By training deep reinforcement learning models, a strategy can be learned that enables IoT devices to select the optimal connection action to meet connection requirements adaptively. With the rapid development of Internet of Things (IoT) technology, more and more devices and systems are connected to the Internet, resulting in massive data and complex interactions. In this context, resource protection and real-time detection have become the key to ensuring the efficient and stable operation of IoT systems. Deep reinforcement learning, as an advanced machine learning technology, provides a new solution for resource protection and real-time detection in the Internet of Things environment. Liang et al. [8] analyzed deep reinforcement learning for resource protection and real-time detection in the Internet of Things environment. Traditional resource protection methods are often based on fixed rules and thresholds, which cannot adapt to the dynamic and changing environment of the Internet of Things. Real-time detection requires efficient and accurate algorithms to process large amounts of data promptly and detect and solve problems. Deep reinforcement learning combines the advantages of deep learning and reinforcement learning and can automatically adjust strategies to adapt to complex and changing environments through learning. In the context of the Internet of Things, deep reinforcement learning can learn device behaviour patterns, predict resource demands, and achieve intelligent resource allocation and protection. Meanwhile, deep reinforcement learning can also build efficient detection models, conduct real-time analysis of IoT data, and promptly detect anomalies and faults.

Renzo et al. [9] explored the intelligent radio environment empowered by reconfigurable intelligent surfaces and analyzed its potential, challenges, and future development directions. A reconfigurable intelligent surface is a planar array that can dynamically adjust its electromagnetic characteristics and intelligently manipulate radio signals through software control. In intelligent wireless environments, reconfigurable smart surfaces play a crucial role. Reconfigurable intelligent surfaces can be synergistically optimized with other components of wireless communication systems to achieve more intelligent communication. Through joint design with components such as transmitters and receivers, RIS can further improve the system's spectral efficiency, energy efficiency, and anti-interference ability. The intelligent wireless environment empowered by reconfigurable intelligent surfaces has enormous potential. Firstly, it can significantly improve the performance and efficiency of wireless communication systems, meeting the growing demand for data transmission. Secondly, the intelligent wireless environment can provide customized communication services for various application scenarios, such as the Internet of Things, autonomous driving, remote healthcare, etc. With the rapid development and widespread application of Internet of Things (IoT) technology, intelligent connections between IoT devices have become a research hotspot. In order to achieve efficient, reliable, and adaptive connectivity of IoT devices, deep reinforcement learning methods have become an important technological approach. Traue et al. [10] explored how to use deep reinforcement learning methods to design intelligent connections in IoT environments. The Internet of Things environment is composed of a large number of heterogeneous devices, which have different communication protocols, functional requirements, and resource limitations. In such an environment, achieving intelligent connections between devices faces many challenges, such as compatibility between devices, communication efficiency, energy management, and so on. Therefore, it is necessary to design an intelligent connection method that can adaptively handle the connection requirements between various devices and ensure the efficiency and stability of the connection.

With the rise of intelligent manufacturing, the level of factory automation and intelligence is constantly improving. Deep reinforcement learning, as an advanced machine learning technology, provides enormous potential for intelligent manufacturing plants. In order to train deep reinforcement learning agents effectively, the digital twin environment has become a key tool. Xia et al. [11] explored how to use digital twin environments to train deep reinforcement learning agents for intelligent manufacturing plants. In the field of intelligent manufacturing, digital twin environments can simulate the entire factory operation process, including equipment, processes, and other aspects. Through the digital twin environment, we can accurately simulate and predict factories, thereby optimizing production processes, improving production efficiency, and reducing production costs. For the training of deep reinforcement learning agents, the digital twin environment provides a secure and controllable learning environment. Agents can make numerous attempts and errors in the digital twin environment without causing any harm to real-world factories. Meanwhile, the digital twin environment can also provide rich data and feedback to help agents learn and optimize. With the continuous progress of technology, the field of indoor environmental design is undergoing unprecedented changes. Traditional design methods can no longer meet the complexity and diversity needs of modern interior design. The computer-aided simulation technology based on 3D CAD modelling has brought revolutionary breakthroughs to indoor environment design. It can not only provide accurate 3D models but also optimize design schemes through simulation analysis, improving the quality and efficiency of design. Yang [12] analyzed interior design optimization based on 3D computer-aided simulation. 3D CAD modelling is the foundation of indoor environment design. Through 3D modelling, designers can more intuitively display the spatial layout, material matching, and decorative details of the design scheme, thereby better communicating with clients and ensuring the accuracy of the design scheme. In addition, 3D modelling can also provide precise data support, providing a foundation for subsequent simulation analysis. Through 3D CAD modelling and simulation analysis, designers can optimize the spatial layout to ensure reasonable utilization and comfort of the space. For example, through simulation analysis, it is possible to predict the lighting conditions, airflow distribution, and personnel flow under different layout schemes in order to select the optimal layout scheme.

Yin et al. [13] explored how to use CAD modelling and reinforcement learning for intelligent trajectory design in unmanned aerial vehicle-assisted communication. Reinforcement learning is a machine learning technique that learns optimal decision strategies through the interaction between intelligent agents and the environment. In unmanned aerial vehicle-assisted communication, unmanned devices can be viewed as intelligent agents, the communication environment as the environment, and the intelligent trajectory is the action path of the intelligent agent in the environment. Through reinforcement learning algorithms, unmanned devices can learn how to choose the optimal trajectory in different environments to achieve communication continuity and stability. By combining CAD modelling with reinforcement learning, it can design more intelligent trajectories for unmanned communication. It uses CAD modelling to build accurate communication environment models, including terrain, obstacles, signal propagation characteristics, etc. Then, these environmental data are used as inputs for the reinforcement learning algorithm to train the agent to learn the optimal trajectory. Through continuous trial and error and adjustment, intelligent agents can gradually learn strategies for selecting the optimal trajectory in different environments. Deep reinforcement learning combines the representation learning ability of deep learning with the decision-making ability of reinforcement learning, enabling it to handle complex and dynamically changing environments. In a 5G ultra-dense network environment, deep reinforcement learning can learn how to allocate policies based on real-time network status and user needs to maximize overall performance. Yu et al. [14] combined deep reinforcement learning with federated learning to achieve intelligent multi-time scale resource environment management in 5G ultra-dense network environments. Specifically, deep reinforcement learning can be used to dynamically adjust resource allocation strategies, while federated learning is used to improve model training efficiency and performance while maintaining data privacy. This combination can make full use of the advantages of both and provide a more effective resource management scheme for multiaccess edge computing in a 5G ultra-dense network environment. Multiaccess edge computing in a 5G ultra-dense network environment is facing the challenge of resource management. By combining deep reinforcement learning and federated learning, we can achieve intelligent multi-time scale resource environment management and optimize network performance and service quality.

Zappone et al. [15] explored the cost perception design of reconfigurable smart surfaces in intelligent wireless environments to achieve more efficient and intelligent wireless communication. Reconfigurable intelligent surfaces are a planar array composed of a large number of low-cost, passive reflective elements that can be controlled and adjusted through software to achieve intelligent manipulation of radio signals. By dynamically adjusting parameters such as phase and amplitude of reflection elements, RIS can achieve beamforming, focusing, scattering, and other effects on the incident signal, thereby improving the performance of wireless communication systems. Based on real-time channel status information and communication requirements, dynamically adjust the parameters of reflection elements to reduce overhead while maintaining performance. For example, when the channel conditions are good, the number of reflection elements can be reduced, or their adjustment frequency can be lowered to reduce computational and communication costs. Cost-aware design is the key to achieving efficient and intelligent applications. By implementing strategies such as adaptive reflection element adjustment, joint optimization algorithm design, and intelligent control signaling design, the cost of RIS systems can be effectively reduced and their performance improved. With the widespread application of wireless communication technology, intelligent interference systems have become a key technology to ensure communication security and optimize network performance. In recent years, reinforcement learning, as a powerful machine learning method, has provided new ideas for the design and implementation of intelligent interference systems. Zhang et al. [16] explored the design and implementation methods of an intelligent interference system environment based on reinforcement learning. Reinforcement learning is a technique that learns through trial and error, with its core being the interaction between intelligent agents and the environment, continuously adjusting strategies to maximize long-term returns. In intelligent interference systems, the interference strategy can be viewed as the behaviour of the intelligent agent, and the communication environment can be viewed as the environment faced by the intelligent agent. Through reinforcement learning, intelligent interference systems can learn how to dynamically adjust interference strategies based on changes in the communication environment to achieve the best interference effect. Train reinforcement learning models using simulated or real communication environment data. By continuously interacting with the environment and adjusting interference strategies, the intelligent interference system can gradually learn the optimal interference method.

3 INTELLIGENT MODEL CONSTRUCTION OF ENVIRONMENTAL DESIGN

As artificial intelligence technology continues to evolve, the field of environmental design is exhibiting distinct trends towards greater automation and intelligence in design processes, increased personalization and humanization of design schemes, as well as a more scientific and comprehensive approach to design evaluation. Before constructing an intelligent environment design model, a thorough analysis of the requirements during the design process is needed. These requirements include improving design efficiency, optimizing design solutions, and meeting personalized user needs. By conducting research on the current situation and challenges in the field of environmental design, it is possible to clarify the problems that intelligent design needs to solve and the expected goals to be achieved. Furthermore, it is essential to take into account the limitations inherent in the real-world design process, including factors like time constraints, budgetary considerations, and material availability. This ensures that the intelligent design model remains both practical and feasible. A crucial step towards achieving intelligent environmental design is the utilization of CAD-based modelling. During this phase, CAD technology must be employed to establish a three-dimensional representation of the environment, specifying the diverse components and their respective characteristics within the model. In order to support intelligent design, it is also necessary to embed intelligent algorithms in the model to achieve automatic generation and optimization of design schemes. Furthermore, it is necessary to establish a mapping relationship between the model and design requirements to ensure that the model can accurately reflect changes in design requirements. The schematic diagram of the 3D modelling technology process is shown below (Figure 1).

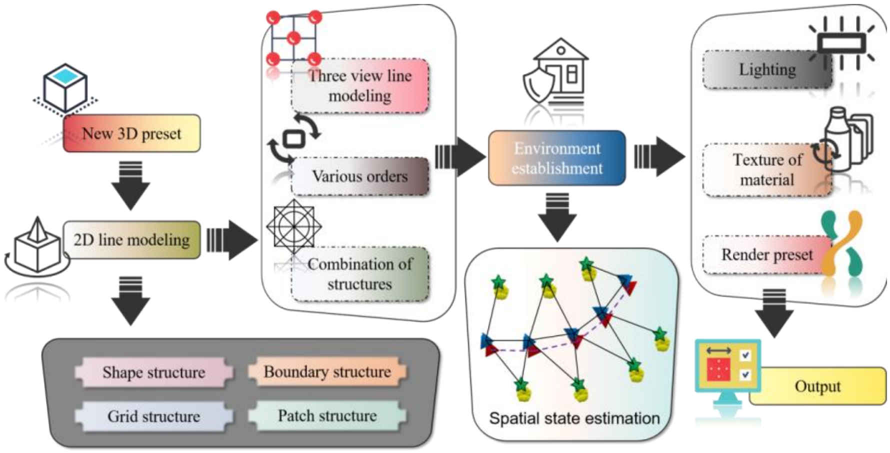

Figure 1: Schematic diagram of 3D modelling technology process.

As an effective machine learning method, reinforcement learning has a wide application prospect in intelligent environmental design. Firstly, this paper defines reinforcement learning elements such as state space, action space, and reward function to describe the state transition and decision-making process in the process of environmental design. Then, select the appropriate reinforcement learning algorithm for training and learning to find the optimal design strategy. Through continuous interaction and trial and error with the environment, the reinforcement learning model can gradually learn the optimal design scheme to meet the design requirements. A common example of the reinforcement learning algorithm is Q-learning, and its updating rules are as follows:

$$Q\ s,a\ \leftarrow Q\ s,a\ +\alpha\left[R\ s,a,s'\ +\gamma\max_{a'}Q\ s',a'\ -Q\ s,a\ \right] \tag{1}$$

Where $Q\ s,a$ is a state-action value function (Q-function), which indicates the expected return of taking action a in the state s ? α It is the learning rate that controls the update step. γ It is a discount factor that is used to weigh the importance of immediate rewards and future rewards.

Reinforcement learning aims to discover the best possible strategy π^* for maximizing the anticipated discounted reward starting from the present state s.

$$V^{\pi}(s) = E\pi\left[\sum_{t=0}^{\infty}\gamma^t r_t \middle| s_0 = s\right] \tag{2}$$

The reward received at the time step t $\gamma \in [0,1]$ is a discount factor, which is used to weigh the importance of immediate rewards and future rewards. In the strategy gradient method, the strategy $\pi\theta$ is represented by a parameterized function, and its parameter is θ. The objective function $J(\theta)$ is defined as the expected discount reward from the initial state distribution:

$$J(\theta) = E_{s_0,a_0,s_1,\ldots}\left[\sum_{t=0}^{\infty}\gamma^t r_t\right] \tag{3}$$

Among them, the action a_t is selected according to the strategy $\pi\theta(\cdot|s_t)$.

In order to evaluate the performance and effect of intelligent environment design, this paper establishes a scientific and comprehensive evaluation index system. The index system should include design efficiency, design scheme quality, user satisfaction, and other aspects. Design efficiency can be measured by comparing the time and cost required for intelligent design and traditional design. The quality of the design scheme can be evaluated by expert review and user feedback. User satisfaction can be obtained through questionnaires and user interviews. By conducting a thorough examination of these indicators, we can assess the strengths, weaknesses, and potential areas for improvement in intelligent environment design. A more detailed experimental analysis will follow.

4 INTELLIGENT ENVIRONMENT DESIGN COMBINING CAD MODELING AND REINFORCEMENT LEARNING

4.1 Implementation Process of Intelligent Environment Design

In intelligent environment design, the combination of CAD modelling and reinforcement learning is the key to realizing the intelligence of the design process. Firstly, the 3D model of the environment is constructed by using CAD modelling technology to provide basic data support for reinforcement learning. Using CAD modelling technology to build a 3D model of the environment can be expressed as:

$$CAD\ \text{model} = f_{\text{CAD}}(\text{Design parameter}) \tag{4}$$

Among them f_{CAD} stands for CAD modelling function, which takes design parameters as input and outputs the corresponding 3D model.

The reinforcement learning algorithm is embedded in the process of CAD modelling to realize the automatic generation and optimization of the design scheme. Specifically, a strategy $\pi(a|s)$ can be defined as the probability distribution of choosing action a in a given state s. The objective of the strategy is to optimize the total accumulated reward, and this can be accomplished through various methods such as solving the Bellman equation, utilizing value iteration, or employing other reinforcement learning techniques.

$$Q^*(s,a) = E_{s'}\left[R(s,a) + \gamma \max_{a'} Q^*(s',a')\right] \tag{5}$$

Where $Q^*(s,a)$ represents the optimal state-action value function. By iteratively updating the Q-value function and strategy, the reinforcement learning model can gradually learn the optimal design scheme that meets the design requirements.

Combining CAD modelling and reinforcement learning algorithm, the intelligent design process can be expressed as:

$$\text{Optimal design scheme} = \mathrm{f}_{\mathrm{RL+CAD}} \text{ Design requirements, user feedback} \tag{6}$$

Among them $\mathrm{f}_{\mathrm{RL+CAD}}$ stands the intelligent design function, which combines reinforcement learning and CAD modelling. It takes design requirements and user feedback as inputs and outputs the optimal design scheme that meets the requirements. In this way, the effective combination of CAD modelling and reinforcement learning can be realized, and the intelligence level of the environmental design process can be improved.

The realization process of intelligent environment design is a comprehensive and iterative process, which covers many key steps from demand analysis to final design scheme output. First of all, requirement analysis is the starting point of intelligent environment design. The main goal of this stage is to define the design objectives and constraints and provide guidance for the subsequent design work. Requirements analysis includes comprehensive consideration of user requirements, functional requirements, performance requirements and environmental constraints. Through in-depth research and user interviews, the design team can obtain key information about user expectations, space usage, aesthetic preferences and budget constraints. This information will be compiled into detailed requirements documents as the basis of design work. Next, CAD modelling technology will be used to build a 3D model of the environment. CAD modelling serves as a widely used technical tool in environmental design, enabling designers to translate abstract concepts into tangible 3D representations. During this phase, designers utilize CAD software to craft a three-dimensional model of the intended environment, drawing from the specifications outlined in the requirements document. This model not only includes static elements such as space layout, material selection, and lighting effects but can also introduce dynamic elements such as furniture layout and pedestrian flow simulation through parametric design.

The 3D model M of the environment can be expressed as the result of CAD software construction according to design parameters P and requirement document D:

$$M = CAD\_Model\ P, D \tag{7}$$

CAD_Model is a CAD modelling function that takes design parameters P (such as size, shape, material, etc.) and requirements document D (including design requirements, space functions, user requirements, etc.) as inputs and outputs the corresponding 3D model M.

Static elements S include fixed components such as spatial layout, material selection and lighting effects, which can be expressed as:

$$S = Static\_Elements\ P_{Static}, D \tag{8}$$

Among them $Static\_Elements$ is a static element modelling function, which creates static elements S according to static design parameters P_{Static} and the requirements document D.

Dynamic element Dyn introduces the parametric design, which allows some parts of the model to change according to specific parameters, such as furniture layout, crowd simulation and so on. These dynamic elements can be expressed as:

$$Dyn = Dynamic\_Elements\ P_{dynamic}, D, \theta \tag{9}$$

$Dynamic\_Elements$ is a dynamic element modelling function that creates dynamic elements Dyn according to dynamic design parameters $P_{dynamic}$, requirements documents D and change parameters θ (such as time, user interaction, etc.).

The final 3D environmental model M_{final} is a synthesis of static element S and dynamic element Dyn:

$$M_{final} = S \cup Dyn \tag{10}$$

Here, the union symbol $\cup$ is used to represent the combination of static elements and dynamic elements in 3D space.

Through CAD modelling, designers can display the design scheme more intuitively and make preliminary evaluations and adjustments. Subsequently, the reinforcement learning algorithm is applied to the design process to optimize the scheme. In intelligent environment design, designers need to define the state space, action space and reward function of design problems and then choose the appropriate reinforcement learning algorithm for training and learning. Through continuous interaction and trial and error with the environment, the reinforcement learning algorithm can gradually learn the optimal strategy to meet the design requirements and generate the corresponding design scheme. Finally, the optimal design scheme that meets the demand is output. After the optimization of the reinforcement learning algorithm, designers will get a series of design schemes that meet the needs. These schemes can be sorted and selected according to different evaluation indexes. Finally, designers need to communicate and confirm with users and relevant stakeholders to ensure that the selected scheme can truly meet users' expectations and needs.

In the whole process of intelligent environment design, it is the key to improve design efficiency and scheme quality to constantly adjust and optimize the model. Because of the complexity and uncertainty of the design problem itself, the initial model and algorithm are often difficult to get satisfactory results directly. Therefore, designers need to pay attention to and adjust the model throughout the whole process, constantly optimize model parameters, improve algorithm strategies and even redesign the model structure according to actual needs and feedback. Through this iterative design method, we can gradually approach the optimal design scheme and improve the efficiency of design work.

4.2 Case Study: Concrete Application of Intelligent Environment Design

To assess the viability and impact of the intelligent environment design model, this section delves into specific use cases. In the realm of smart home design, CAD modelling is employed to build a three-dimensional representation of the domestic space, specifying the attributes and capabilities of diverse smart devices. Reinforcement learning algorithms are then leveraged to refine the design approach, aiming to enhance user comfort while promoting energy efficiency. A comparative analysis with traditional design techniques reveals the strengths and potential refinements of the intelligent design approach. Illustrative examples are presented in Figures 2 and 3.

Figure 2: Design case of the traditional method.

Figure 3: Design case of this method.

To validate the practical worth and potential of intelligent environment design, this paper conducted a user rating experiment. The study enrolled 130 participants with varying backgrounds, ages, and genders, ensuring a diverse and representative sample. All participants possessed some knowledge or interest in smart homes. They were tasked with evaluating smart home cases created using both traditional design methods and the intelligent environment design approach proposed in this paper.

During the experiment, participants were first briefed on the experiment's objectives and scoring criteria. Subsequently, they were randomly assigned to score one of two sets of cases. To guarantee impartial scoring, the experiment employed a double-blind design, meaning both participants and researchers were unaware of which cases were designed using traditional methods and which employed intelligent techniques. Figure 4 presents the detailed scoring outcomes.

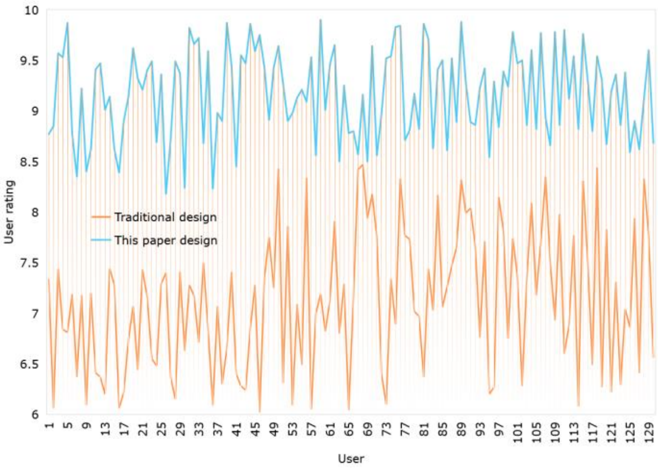

Figure 4: User rating results.

After the experiment, we collected the rating data of users and made a statistical analysis. The results show that users' scores on smart home cases designed by the intelligent environment design method proposed in this paper are significantly higher than those designed by traditional design methods.

Specifically, the average score of the intelligent design method reached 9.3 points, while the average score of the traditional design method was only 7.5 points. This result shows that the intelligent environment design method proposed in this paper can better meet the needs and expectations of users. This is because the intelligent design method fully considers the needs and constraints of users in the design process and optimizes the design scheme by using a reinforcement learning algorithm. In contrast, traditional design methods may pay more attention to the designer's personal experience and subjective judgment while ignoring the actual needs and feedback of users.

In conclusion, the findings of this study unequivocally highlight the promise and practical significance of intelligent environment design. The integration of CAD modelling technology with reinforcement learning algorithms in intelligent design methods leads to notable enhancements in design efficiency and quality, thereby better aligning with user needs and expectations.

5 SIMULATION EXPERIMENT OF INTELLIGENT ENVIRONMENT DESIGN

5.1 Simulation Experiment and Analysis

In order to verify the effectiveness and feasibility of the intelligent environment design model, this section carries out simulation experiments. Firstly, based on CAD modelling technology, 3D models of multiple environmental design scenes are constructed. Then, the reinforcement learning algorithm is used to optimize the design scheme of these scenes to meet different design requirements and constraints. During the simulation experiment, the changes in various design parameters, such as design time, cost and user satisfaction, are recorded for subsequent result analysis. In the implementation of the simulation experiment, this paper uses the control variable method to observe the performance of the intelligent design model by changing different design parameters and constraints. Furthermore, a control group experiment was set up to compare the intelligent design model with the traditional design method to evaluate its performance more comprehensively. All experimental data are strictly processed and statistically analyzed to ensure the reliability of the results.

In order to make a fair comparison, this section sets the same design tasks for the two design methods, including different spatial layouts, functional requirements and aesthetic standards. The design efficiency of the two design methods is shown in Figure 5.

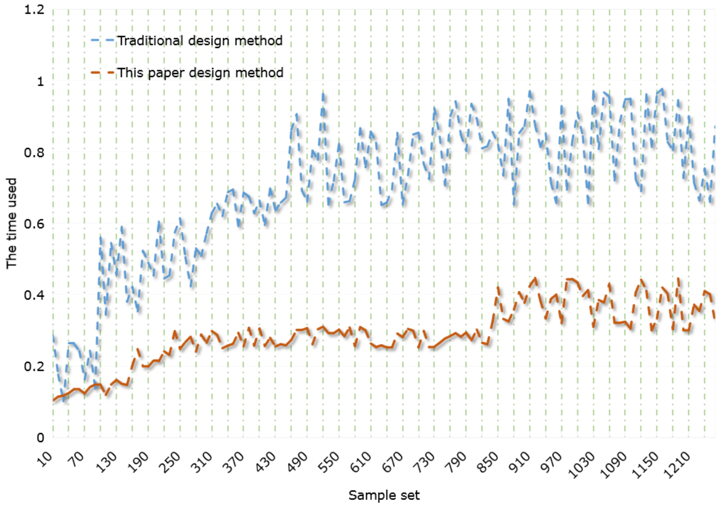

Figure 5: Design efficiency.

When it comes to design efficiency, the intelligent environmental design model outperforms traditional methods by significantly reducing design time—roughly 40%. This advantage stems from the model's ability to automatically navigate the design space and swiftly produce multiple viable design options, eliminating the need for designers to manually iterate and refine as often required in traditional approaches. Additionally, this model exhibits self-learning and self-adaptation capabilities. Through constant user interaction and feedback loops, it progressively comprehends user needs and tastes, enabling real-time adjustments to the design plan based on this valuable input. This dynamic feedback and adjustment process not only streamlines the design workflow but also enhances accuracy, eliminating the need for repetitive modifications and trial-and-error cycles common in traditional design practices. A comparison of design quality is visualized in Figure 6.

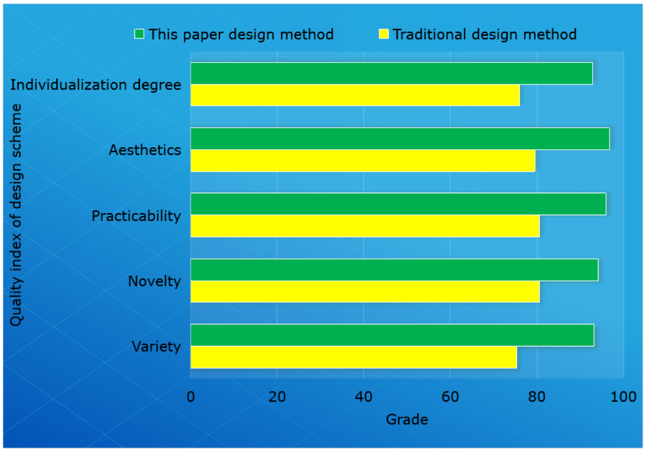

Figure 6: Quality comparison of design schemes.

In terms of scheme quality, the scheme generated by the intelligent design model is superior to the traditional method in diversity and innovation. This is due to the powerful search and optimization ability of the reinforcement learning algorithm, which enables the model to explore more innovative design schemes while meeting the constraints. User satisfaction is shown in Figure 7.

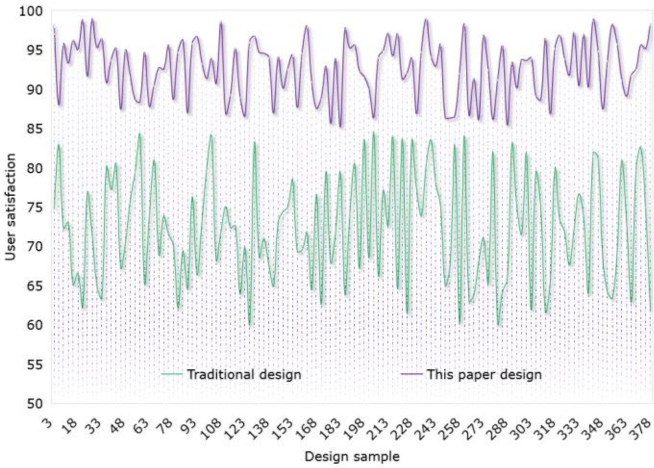

Figure 7: User satisfaction.

In terms of user satisfaction, users' satisfaction with the intelligent design model is obviously higher than that of traditional methods. Specifically, the user satisfaction of the traditional design method is about 73%, while the user satisfaction of the intelligent design method is as high as over 90%. This significant difference reflects the superiority of the intelligent design model in meeting the needs of users. The reason why the intelligent design model can significantly improve user satisfaction is that it better understands and meets user needs. Traditional design methods often focus on the designer's aesthetics and experience and may not fully consider the actual needs and expectations of users. By combining user feedback and reinforcement learning algorithms, the intelligent design model can capture users' needs more accurately and optimize the design scheme according to these needs, thus providing an environment design that is more in line with users' expectations. Furthermore, the real-time feedback and adjustment mechanism of the intelligent design model is also one of the key factors to improve user satisfaction. In the traditional design method, users usually need to see the final effect after the design is completed. At this time, if they find something unsatisfactory, they often need to make tedious modifications and adjustments. The intelligent design model can interact with users in real time during the design process and adjust the design scheme in time according to users' feedback. This immediacy and interactivity greatly enhance users' sense of participation and satisfaction.

Through the analysis of the simulation experiment data, this paper finds that the intelligent environment design model has obvious advantages in design efficiency, scheme quality and user satisfaction. Specifically, compared with the traditional design method, the intelligent design model can greatly shorten the design time, reduce the design cost, and improve the diversity and innovation of the design scheme. In addition, the improvement in user satisfaction also verifies the effectiveness of intelligent design in meeting individual needs.

5.2 Enlightenment of Simulation Experiment on Intelligent Environment Design

This paper gains significant insights from its simulation experiments:

Firstly, the integration of CAD modelling technology with reinforcement learning algorithms emerges as a powerful approach to intelligent environmental design. CAD modelling offers precise 3D representations and data for design, while reinforcement learning autonomously refines designs through iterative learning. This synergy not only leverages the strengths of both technologies but also paves the way for more advanced design intelligence. Future explorations could involve deep learning's enhancement of CAD modelling intelligence or the development of more sophisticated reinforcement learning algorithms for complex design scenarios.

Secondly, a crucial aspect of enhancing intelligent design effectiveness lies in thoroughly considering user needs and constraints during the design process. These elements are pivotal in determining design feasibility and user satisfaction. Intelligent design processes must incorporate user research and data analysis to translate user requirements and limitations into design optimization objectives. This ensures that designs not only align with user needs but also adhere to various constraints, thereby enhancing their practicality and viability.

Lastly, the performance and efficiency of intelligent design can be further elevated through continuous optimization and adjustment of model parameters. This complex system's performance is influenced by numerous factors, including model parameters, algorithm choice, and data quality. To achieve optimal design outcomes, it's essential to refine the model by improving algorithms, optimizing parameters, and enhancing data quality. Additionally, staying abreast of technological advancements and promptly applying them to intelligent design models is crucial for maintaining their cutting-edge competitiveness.

6 CONCLUSIONS

In this study, we successfully constructed an intelligent environment design model that combines CAD modelling with reinforcement learning technology. Through simulation experiments, we confirmed its feasibility and effectiveness, revealing its superiority over traditional design methods in terms of efficiency, quality, and user satisfaction.

Our contributions to the intelligent field of environmental design are threefold. Firstly, we introduced a novel approach that integrates CAD modelling and reinforcement learning, offering a fresh perspective for the field's intelligent development. Secondly, our simulation experiments validated the model's feasibility and effectiveness, providing valuable insights for researchers in related domains. Finally, our findings are expected to advance the field's intelligent processes, enhance design efficiency and quality, cater to users' personalized needs, and foster harmonious development between environmental design and human life.

Despite our achievements, there are still areas for improvement. Currently, the model faces limitations when handling complex scenes and large datasets. Furthermore, further research is needed on optimizing model parameters and improving algorithms. Additionally, we have not fully considered the impact of user feedback and changing demands on intelligent design. To address these issues, future research should aim to expand the model's application scenarios and data scale, delve deeper into model optimization and algorithm enhancement, and explore the influence of user feedback and demand changes on intelligent design.

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